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Conditional vs. Unconditional Efficiency in Beta Forecasting: Methods and Evidence

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Abstract

Based upon the concepts of conditional vs. inconditional efficiency, it is shown that both accounting-based and market-based beta forecasts contain important information to forecast the beta coefficients. Composite-based beta forecasts are also proposed to reduce the MSE of beta forecastings.

I. Introduction

The importance of accounting information in forecasting beta coefficients has been investigated by the finance and accounting professions in the last one and a half decades. However, the results obtained have been inconclusive. The main purposes of this paper are: (i) to review and critique previous research related to market vs. accounting information in beta forecasting; (ii) to propose a new method to test whether accounting information is useful in forecasting beta coefficients; and (iii) to construct a composite prediction to reduce the mean square errors (MSE) of beta coefficient forecasts. In the second section, previous researchs related to beta forecasting are briefly reviewed. In the third section issues related to evaluating the performance of forecasts are explored. In particular, the decomposition of MSE proposed by Mincer and Ziarnowitz (1969) is discussed in relation to its application to beta forecasting, as suggested by Klemkosky and Martin (1975). Possible gains of using composite forecasts are discussed in terms of the concepts and methods suggested by Bates and Granger (1969) and Granger and Newbold (1973). In the fourth section two alternative beta forecasts are examined, in accordance with historical researchs, as discussed in section II. Relative advantages between accounting base and market base forecasting are discussed in accordance with the concepts of conditional efficiently are discussed in section V. Empirical investigations of testing the importance of accounting information in forecasting beta, and evaluating the performance of using both accounting and market information are explored. Finally, results of this paper are summarized and our conclusions are indicated.

II. Previous Researchs in Beta Forecasting

There are two alternative methods for beta forecasting market-based and accounting-based beta forecasting. The market-based approach to beta forecasting does not rely upon accounting risk measures, and the accounting-based beta forecasting method does include the accounting risk measures in the beta forecasting process. Beaver et. al., (1970), Eskew (1979) and others have shown that the inclusion of accounting-based measures in models used to predict the systematic risk of equity securities enables better predictions than security-market-based models which exclude accounting risk measures. However, more recently Elgers (1980) has argued that accounting-based forecasts are not superior to the market-based prediction. He uses the instability over time of systematic risk and the "shrinking effect" to support his conclusion. However, this argument is not necessarily an objective criteria to determine whether accounting-based risk prediction can give additional information in the beta forecasting process. In the next section some basic concepts related to evaluating and combining alternative forecasts are discussed. The purpose is to show how the usefulness of accounting information in forecasting beta can be statistically tested.

III. The Evaluation and Combination of Forecasts

In any forecasting exercise, it is clearly important to evaluate the quality of predictions made, using post-sample data. A number of specific proposals for doing this have been made, and implemented in the literature. Many of the approaches to forecast evaluation are discussed at some length in Granger and Newbold (1973), and in Chapter 8 of Grange and Newbold

(1977). This section, which relies heavily on these references, introduces our approach to the evaluation of beta forecasts.

Let F_i $(i=1,2,\ldots,N)$ be a set of forecasts, and X_i $(i=1,2,\ldots,N)$ be the corresponding true values. Mincer and Zarnowitz (1969) propose estimating the regression model

$$X_i = a + b\,F_i + \varepsilon_i \tag{1}$$

where ε_i is an error term. The forecasts are then said to be "efficient" if a=0 and b=1. In practice, then, one tests for "efficiency" by fitting the model (1) and using the usual F-test of the null hypothesis that both a is 0 and b is 1. In fact, this suggestion corresponds to a proposed decomposition of mean squared forecast error, due to Theil (1958). This involves computing the three terms on the right-hand side of

$$\frac{\sum_{i=1}^{N} (X_i-F_i)^2}{N} = (\bar{F}-\bar{X})^2 + (s_F - r\,s_x)^2 + (1-r^2)\,s_x^2 \tag{2}$$

where $\bar{F}$ and $\bar{X}$ are the sample means, s_F and s_x the sample standard deviations, and r the sample correlation between predicted and actual. The "efficiency" concept of Mincer and Zarnowitz corresponds to a requirement that the first two terms on the right-hand side of (2) not be "too large". Viewed in this light, we see that "efficiency" merely implies that the forecasts have the "right" mean--that is, that they be unbiased--and variance. Notice that this does <u>not</u> imply that the variance of the forecasts should be the same as that of the actuals. Indeed, to the extent that the two are not perfectly correlated, the former variance should optimally be smaller than the latter.

Granger and Newbold (1973) have critized the Mincer-Zarnowitz definition of efficiency on the grounds that it really says very little about forecast quality. All that is required is that the F_i have smallest mean squared error among the class of predictions $a+b\ F_i$. Thus, a set of forecasts would be very poor predictions indeed, and yet be deemed "efficient" under this definition. Granger and Newbold argue that, in order to effectively evaluate a set of forecasts, in terms of mean squared error for example, with an alternative set of forecasts. Hence, a set of forecasts F_{1i} (i=1,2,...,N) could be evaluated against a competing set F_{2i} (i=1,2,....,N). This is quite common practice in econometrics, where model-based forecasts are often compared with naive single series time series extrapolutions. However, simply because the forecasts F_{1i} outperform F_{2i} one should not take this as necessarily implying efficiency. It may still be the case that the F_{2i} contain useful information not present in F_{1i}. This notion led Granger and Newbold (1973) to a definition of <u>conditional efficiency</u>. Suppose that the forecasts F_{1i} and F_{2i} are "efficient" in the sense of Mincer and Zarnowitz, and consider the regression model

$$X_i = k\ F_{1i} - (1-k)\ F_{2i} + \varepsilon_i \tag{3}$$

or, equivalently,

$$X_i - F_{2i} = k\ (F_{1i}-F_{2i}) + \varepsilon_i$$

In fitting the model (3), we are entertaining, following Bates and Granger (1969), the possiblity of a composite, or <u>combined</u>, forecast which is a weighted average of the two individual forecasts. If F_{2i} contains no useful information about X_i, which is not propoerly incorporated in F_{1i}, the optimmal value of k of (3) in the composite is 1. In that case, Granger and Newbold define F_{1i} as conditional efficient which respect to F_{2i}.

If we have available a pair of forecasts, and neither is conditionally efficient with respect to the other, then it is possible to find a combined forecast which outperforms each individual forecast, in the near squared error sense. Some empirical research on the combination of forecasts is given in Newbold and Granger (1974).

The estimation of the model (3), then, has two possible advantages. First, it can provide a stringent criterion against which to evaluate a set of forecasts. Further, it may lead to the development of a superior predictor.

Now, this idea can be extended to allow for the possbility that the individual forecasts are not efficient in the Mincer-Zarnowitz sense. Amalgamating the ideas behind (1) and (3), we could fit the regression model

$$X_i = a + b_1 F_{1i} + b_2 F_{2i} + \varepsilon_i \tag{4}$$

If the forecasts F_{1i} are both Mincer-Zarnowitz efficent and conditionally efficient with respect to F_{2i}, we would have, in (4), a=0, b_1=1, b_2=0. Variants of this kind of hypothesis have been tested and discussed by Nelson (1972) and Hatanaka (1974).

Our discussion suggests, then, that, having fitted the model (4), two null hypothesis might be tested. These are

$$H_{01}: \; a = 0, \; b_1 = 1, \; b_2 = 0$$

as discussed in the previous paragraph, and

$$H_{02}: \; a = 0, \; b_1 + b_2 = 1$$

which implies the simple weighted average model (3).

Given two sets of forecasts, then, we might conclude either that one has no useful information not present in the other, or that a superior forecast can be achieved by using a linear function of the individual forecasts. In the following section these ideas are applied to forecasts of beta, based respectively on market information and accounting information.

IV. Some Empirical Results

In this section, the composite forecasting method discussed in section III is used to objectively determine whether accounting-based risk measures are useful in forecasting market beta. Data from 250 firms for the period 1961-1980 are used in the empirical investigation. The sample period is devided into two subsample periods, the first subsample period is 1961-1970 and the second subsample period is 1971-1980.

To perform the hypotheses tests discussed in the previous section, we need the actual beta for both subperiods and two alternative beta forecasts for the second subperiod. Two alternative beta forecasts will be obtained (i) non-accounting-based predictions and (ii) accounting-based predictions. Following Elgers (1980), these two predictions are now specified.

(1) Non-accounting Predictions

Two naive (market data only) beta forecasts serve as the first beta forecast. These two forecasts are also used as benchmarks to evaluate the accounting variable (AV)-based risk predictions, as suggested by Elgers. The following notation is employed:

(i) β_{OLS} = ordinary least squares beta estimate.

(ii) β_{V} = Bayesian adjusted beta in accordance with the procedure of Vasicek (1973)

Summary statistics of market risk used in this study are listed in Table 1.

(2) Accounting-based Predictions

To compute accounting based forecasts, we need to specify dependent variables and independent variables. Two beta estimates, i.e., β^2_{OLS} and β_V as indicated in Table 1 are used as dependent variables. Fifteen accounting-based risk measures, as indicated in Table 2, are used as explanatory variables in constructing the accounting-based predictions. These variables are included to reflect basically four determinants of equity beta (leverage, size, variability, and covariability determinants). To determine the independent variables to be included in the accounting-based prediction model. The stepwise regression procedures was used to select a model. Results of stepwise regression for the two alternative dependent variables are listed in Table 3. These two models are used to estimate two alternative AV beta forecasts. To calculate the means-square-errors (MSE) decompositions as indicated in equation (2), both market-based and accounting-based betas are used as inputs. Empirical results of both aggregated and disaggregated MSE are calculated and listed

TABLE 1

Market Risk: Summary Statistics

	Correlation			Mean	Standard Deviation
	B^1_{OLS}	βv	B^2_{OLS}		
B^1_{OLS}	1.000			1.168	.334
β_v	.9915	1.00		1.154	
B^2_{OLS}	.5476	.552	1.00	1.150	.288

Remarks: B^1_{OLS}: period one OLS beta

β_v : Vasicek's bayesian adjusted beta

B^2_{OLS}: period 2 OLS beta.

TABLE 2

Descriptive Statistics of Candidate Independent Variables (1961-1970)

No.	Variable	Mean	Standard Deviation
1.	Financial leverage, book values	.462	.147
2.	Sales	5.843	1.299
3.	Assets	5.708	1.340
4.	Dividend payout	.489	.163
5.	Asset growth	.106	.060
6.	Current ratio	2.722	.959
7.	Quick ratio	1.521	.728
8.	Variability of return on net worth	.077	.312
9.	Variability of sales to net asset	.144	.128
10.	Operating leverage, definitional	.723	.152
11.	Operating income beta (deflated)	.899	1.342
12.	Sales beta, covariance form	.836	2.070
13.	Asset growth (regression)	.122	.074
14.	Sales growth (regression)	.112	.075
15.	Operating income beta	1.350	3.304

TABLE 3

Summary of Stepwise Regression Results

Dependent:	B_{OLS}	β_V
Adjusted R^2	.2453	.2364
Independent variables Coefficients and (t values)		
Constant	.9112 (11.920)	1.037 (12.712)
Financial leverage	.704 (5.308)	.599 (5.807)
Dividend payout	-.175 (-3.502)	-.108 (-2.848)
Sales beta	.0299 (3.015)	.0176 (2.277)
Operating income beta	-.0114 (2.180)	.0257 (2.276)
Assets	---	-.026 (-2.414)

in Table 4. Results of Table 4 are similar to Elgers' MSE decomposition. Elgers used "shrinking factor" and the instability of beta to argue that the superior predictive ability of accounting-based forecsats are misleading. On the next section the usefulness of composite-based forecastings is empirically tested.

V. Composite-based Forecasts

To test the null hypotheses following from equation (4), results obtained from the OLS approach are listed in Table 5 and the results using the Vasicek (1973) approach are listed in Table 6. In addition regression results related to equation (3) are listed in Tables 7(a) and 7(b).

In terms of our discussion in section III these results are extremely interesting. Consider, first, the two sets of forecasts obtained from the OLS approach. We saw, in Table 4, that, in terms of mean-squared prediction error, the accounting-based forecasts are superior to the market-based forecasts. The respective mean squared errors are .0677 and .0893. However, turning to Table 5, we see that a further reduction, to .0545, can be achieved in mean squared forecast error by using a predictor which is a linear composite of the two individual predictors. It can be seen that the estimated coefficients on both the accounting-based and market-based forecasts are statistically significant, leading to the conclusion that neither individual predictor is efficient with respect to the other in the sense of Granger and Newbold. Thus, we infer that, in spite of its inferior preformance, the market-based forecast contains useful information that is not present in the accounting-based forecast.

TABLE 4

Prediction Results

Dependent	Naive B_{OLS}	Naive β_v	ARS B_{OLS}	ARS β_v
mean prediction (β_p)	1.1686	1.1535	1.1686	1.1535
correlation (β_p, β_a)	.5486	.5821	.4519	.4772
Standard deviation of prediction (Sp)				
MSE Decomposition				
Bias	.0003	.0000	.0003	.0000
Inefficiency	.0309	.0090	.0015	.0001
Random error	.0581	.0577	.0658	.0638
TOTAL MSE	.0893	.0667	.0677	.0640

TABLE 5

Weighted Average of Betas - OLS Approach

	Intercept	$\hat{\beta}^{A}_{OLS}$	β^{1}_{OLS}
coefficients	0.25073	0.39885	0.37034
STD. Errors	0.10384	0.10206	0.051782
T-ratios	2.414537	3.907934	7.15056

M.S.E. = 0.0545

TABLE 6

Weighted Average of Beta - Vasicek Approach

	Intercept	$\hat{\beta}_v^A$	β^1_{OLS}
Coefficients	-0.09642	0.60568	0.47454
STD. Errors	0.13389	0.13338	0.066926
T-ratios	-0.720127	4.540995	7.090486

M.S.E. = 0.0530

TABLE 7

Results of

$$X_j - F_{2i} = k\,(F_{1i} - F_{2i}) + \varepsilon_i$$

(a) OLS Approach

	k
Coefficient	0.6297
T-ratio	12.001

M.S.E. = 0.0566

(b) Vasicek Approach

	k
Coefficient	0.5255
T-ratio	7.874

M.S.E. = 0.0534

It further emerges from Table 5 that, when the model (4) is fitted to these data, the estimated intercept term differs significantly from zero, and the sum of the estimated partial regression coefficients is considerable less than one. This suggests inefficiency in the Mincer-Zarnowitz sense, and is reflected in a statistically significant increase in mean squared error when the model (3) is filled, as can be seen in Table 7(a).

We turn now to the results based on the Bayesian adjustment of Vasicek. We see in Table 4 that, here, the individual performances of the accounting-based and market-based beta forecasts are very similar. Their respective mean squared errors are .0640 and .0667. However, we find from Table 6 that, once again, a substantial reduction in mean squared prediction error--to .0530--can be obtained through the use of a composite predictor. The estimated coefficients on both the market-based and accounting-based forecasts are statistically significant, so that once more we can infer that neither individual predictor is conditionally efficient with respect to the other. We further see from Table 6, by contrast with the OLS approach, that in this case the estimated intercept does not differ significantly from zero. Moreover, the sum of the two estimated partial regression coefficients is close to one. This suggests that the simpler model (3), implying a composite forecast which is a weighted average of the two individual, would be appropriate. This is confirmed by the results in Table 7(b), showing only a very small increase in mean squared error when the simpler model is used.

VI. Conclusions

In this paper, we have followed a number of other authors in comparing forecasts of beta, based respectively on accounting and market information. However, rather than merely asking which set of forecasts is superior, we have gone further and investigated the possbility of using a composite forecast. This approach allows us to test whether, irrespective of their individual performances, one set of forecasts contains useful information not present in the other. We examined the use of ordinary least squares estimates of the betas, and estimates obtained from the Bayesian adjustment. Qualitatively our findings were similar in each case: neither set of forecasts was found to be conditionally efficient with respect to the other. We thus infer that each set of forecasts contains some useful information about beta that is not present in the other. Thus, the debate as to whether accounting-based or market-based forecasts of beta are the more accurate seems to have ignored an extremly important point. It is not necessary to restrict attention exclusively to one of these forecasts or the other. Rather, it is possible to achieve superior forecasts by combining the two. Since this is possible, we can infer that neither individual forecast efficiently incorporates all of the available useful information about future betas.

One important difference emerged in our analyses of the OLS and the Bayesian-adjustment cases. Only in the latter was it possible, without significant loss of forecast efficiency, to restrict attention to a composite predictor that is a simple weighted average of the individual forecasts. It thus seems desirable that the Bayesian adjustment be carried out. In that case, as can be seen in Table 7, the composite forecast can be formal as a weighted average, giving weight 0.53 to the accounting-based forecast and 0.47 to the market-based forecast. Our empirical analysis indicate that this simple composite predictor yeilds beta forecasts that are, in the aggregate, significantly more accurate than any set of individual forecasts that we have examined.

In summary, then, our study has indicated that accounting-based and market-based forecasts can be combined in the production of superior composite forecasts of beta. Accordingly, we conclude that each type of forecast embodies useful information not present in the other.

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